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(SYNOPSIS FOR REGISTRATION FOR DEGREE OF DOCTOR OF PHILOSPHY IN COMPUTER SCIENCES)

Proposed Topic	:	A Study of Financial Time Series forecasting using Wavelet Neural Networks
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1. Background:

A time series is a sequence of data points, measured typically at successive times spaced at uniform time intervals. Examples of time series are the daily closing value of the Stock market index or the annual flow volume of the River. Time series *analysis* comprises methods for analyzing time series data in order to extract meaningful statistics and other characteristics of the data. Time series *forecasting* is the use of a model to forecast future events based on known past events to predict data points before they are measured.

A time series model will generally reflect the fact that observations close together in time will be more closely related than observations further apart. In addition, time series models will often make use of the natural one-way ordering of time so that values for a given period will be expressed as deriving in some way from past values, rather than from future values[5,10]. Financial time series such as stock market index, exchange rate etc are inherently non-stationary, it is regarded as one of the most challenging applications of time series forecasting.

Whilst non-linear models are often used for a variety of purposes, one of their prime uses is for forecasting, and it is in terms of their forecasting performance that they are most often judged. However, a casual review of the literature suggests that often the forecasting performance of such models is not particularly good. The relatively poor forecasting performance of some non-linear models calls for substantive further research in this area, given that one might feel uncomfortable asserting that non-linearities are unimportant in describing economic and financial phenomena[38]. The work that we propose here can be viewed as a contribution to this field of research. We shall apply Wavelet Neural Networks for financial time series forecasting with regard to certain parameters and expect better results than other techniques such as Fourier methods, numerical techniques and neural networks etc.

2.1 Literature Review:

The combination of wavelet theory and neural networks has lead to the development of wavelet networks. Wavelet networks are feed-forward neural networks using wavelets as activation function. In wavelet networks, both the position and the dilation of the wavelets are optimized besides the weights. Wavelets are a class of basic functions with oscillations of effectively finite duration that makes them look like little waves, self similar; multiple resolution nature of wavelets offers a natural framework for the analysis of physical signals. Using theoretical features of the wavelet transform, network construction can be developed. These methods help to determine the neural network parameters and the number of hidden neurons during the training. There are two main approaches to form wavelet networks. In the first approach, the wavelet component is decoupled from the learning component of the perceptron architecture. In essence, a signal is decomposed on some wavelet and the wavelet coefficients are fed to the neural network. In the second approach, the wavelet theory and the neural network are combined into a single method. The basic neuron of a wavelet network is a multidimensional wavelet, in which the dilation and the translation coefficients are considered as neuron parameters. The output of a wavelet network is therefore a linear combination of several multidimensional wavelets[26].

The origin of wavelet networks can be traced back to the work by Daugman [13] in which Gabor wavelets were used for image classification. Wavelet networks have become popular after the work by Pati [40,41], Zhang and Benveniste [76], and Szu [52]. Wavelet networks were introduced as a special feed forward neural network. Zhang did apply wavelet networks to the problem of controlling a robot arm. As mother wavelet, they use the function

$$\psi(x) = (x^{T} \cdot x - \dim(x)) \cdot e^{-1/2\, x^{T} \cdot x}$$

Szu took a different function, $\cos(1.75\, t) \exp(-t^{2}/2)$, as mother wavelet for classification of phonemes and speaker recognition. Simple combinations of sigmoids were chosen by Pati [41]. This approach has been generalized by Fernando Marar [20] to polynomial functions of the sigmoid function. For classification the ouput may be taken as $\sigma(f(\mathbf{x}))$, with σ the sigmoid function [52].

A motivation for using wavelet networks is that there are universal function estimators that may represent a function to some precision very compactly. This follows from the work by Hornik [24] and Kreinovich [33]. From the practical point of view, the determination of the number of wavelets and their initialization represents a major problem with wavelet networks. A good initialization of wavelet neural networks is extremely

important to obtain a fast convergence of the algorithm. A number of methods have been implemented. Zhang [76] initializes the coefficients with an orthogonal least-squares procedure. As an alternative, the dyadic wavelet decomposition may be used to initialize the network. Echauz [16] applies a clustering method to position the wavelets. The distribution of points about a cluster permits to approximate the necessary dilation of the wavelet.

Echauz [17] proposes also an elegant method using trigonometric wavelets. He uses functions of the form:

$$\cos \text{trap}(x) = \cos(3\pi/2 \cdot x) \cdot \min\{\max\{3/2 \cdot (1-|x|),0\}, 1\}$$

Trigonometric wavelets can be approximated by polynomials. Fitting of the polynomial is a linear problem that is solved more easily than fitting trigonometric wavelets. The fitting parameters of the polynomials can be used to approximate the initializing parameters of the corresponding wavelets. In Boubez [6], the network is initialized by positioning and approximating first low resolution wavelets. New higher resolution wavelets are introduced and initialized subsequently to minimize the score. Rao [47] uses the principle of cascade correlation learning architecture to train the network. New wavelets are added one by one and at each step, the network is trained till convergence is reached. Yi-Yu [68] opts for the opposite approach; the wavelet network uses first a large number of functions. The wavelet network is made subsequently as compact as possible using a shrinkage technique to delete not too important nodes. Back propagation algorithms, conjugate gradient method [52] stochastic gradient algorithm [76] or genetic algorithms [44] are used for training the network. A number of interesting applications have taken advantage of the multiresolution properties of wavelet networks. Many manufacturing process monitoring systems have the function of detecting abnormal vibrations [42]. For vibration detection and classification, wavelet-based methods represent good alternatives to Fourier analysis.

Wavelet networks have been implemented with success to identify and classify rapidly varying signals, for instance to identify high risks patients in cardiology [14] or for echo cancellation [36]. Major efforts have been undertaken in the field of speech segmentation and speaker recognition following the pioneering work by Szu et al. [51-52]. Wavelet networks have been tested on a number of classical control problems, from the detection of small variations in a plant to the control of robotics arms [31].

An interesting alternative to wavelet networks consists of using a dictionary of dyadic wavelets and to optimize only the weights w_i. This approach is generally referred to as wave-net or wavenets. It was first proposed by Bakshi et al. [6]. Dyadic wavelet network or wavenets were first proposed by Bakshi et al. [6]. In its simplest version, a wavenet corresponds to a feed forward neural network using wavelets as activation functions.

$$u(x) = \sum_{n,m} d_{n,m} f_{n,m}(x) + \bar{u}$$

Where $\bar{u}$ is the average of u, $d_{n,m}$ are the coefficients of the neural network and $f_{n,m}$ are the wavelets .

In 1993, Bakshi and Stephanopoulos, proposed the mathematical framework for the development of Wave-Nets and discussed various aspects of their practical implementation in [7]. They have shown that the training and adaptation efficiency of wave nets is at least an order of magnitude better than other networks. Two types of neuron models were proposed by Yamakawa et. al [65], *wavelet synapse neuron* and *wavelet activation function neuron*, which are obtained by modifying a traditional neuron model with non-orthogonal wavelet bases. Zhang and Walter [76] described a wavelet based neural network similar to the radial basis function network, except that the radial basis functions are replaced by orthonormal scaling functions. They have shown that the wavelet network has universal and L^2 approximation properties and is a consistent function estimator. Hierarchical neural networks were proposed by Kollias [50] as an efficient architecture for classification or retrieval of multiresolution invariant image representations. Multiresolution image analysis was used to reduce the size of these representations in an optimal way, based on auto associative linear networks.

Inspired by the theory of multiresolution analysis of wavelets and artificial neural networks, a multiresolution neural network for approximating arbitrary nonlinear functions was proposed by Ying and Zhidong in [71]. As the multiresolution neural network consists of a scaling function neural network and a set of sub-wavelet neural networks, in which each sub-neural network can capture the specific approximation behavior at different resolution of the approximated function. They have designed a hierarchical construction algorithm which gradually approximate unknown complex nonlinear relationship between input data and output data from coarse resolution to fine resolution. Furthermore, they have proposed a new algorithm based on immune particle swarm optimization to train multiresolution neural network. In 2006, Vicente and Javier [60], proposed a multiresolution finite-impulse-response (FIR) neural-network-based learning algorithm using the maximal overlap discrete wavelet transform (MODWT) The multiresolution learning algorithm employs the analysis framework of wavelet theory, which decomposes a signal into wavelet coefficients and scaling coefficients. The translation invariant property of the MODWT allows aligment of events in a multiresolution analysis with respect to the original time series and, therefore, preserving the integrity of some transient events. A learning algorithm was also derived for adapting the gain of the activation functions at each level of resolution. In 2007, Zakeri et. al. [75], studied the real time on-line learning of an experimental thermal process based on on-line wave-nets with localized and hierarchical multi-resolution learning. In 2008, Aadaleesan et. al. [1] with the use of Laguerre basis filters coupled with a wavelet network in Wiener type model structure are capable of modeling highly nonlinear systems with acceptable accuracy. Use of Laguerre models for mildly nonlinear system is possible only with a piece-wise linear models. Wavelet basis functions have the property of localization in both time and frequency and they can approximate even severe nonlinearities with appreciable accuracy with fewer model terms. But wavelet approximations fail miserably, in terms of model parsimony, if used for approximating linear or mildly nonlinear systems. Mahmood et.al [37] proposed a technique that uses wavelet multiresolution analysis (MRA) and neural networks for the detection and classification of transients in a power system. The simulation results show that the proposed method is simple, accurate and reliable to automate the procedure of classification of power system transients. Turgay and Kerem [59] predicted the daily precipitation from meteorological data using the wavelet–neural network method, which combines two methods: discrete wavelet transform and artificial neural networks. The results indicate that wavelet–ANN model estimations are significantly superior to those obtained by either a conventional ANN model or a multi linear regression model.

2.1 Related Work

In the past two decades, considerable research efforts have been focused on forecasting exchange rates using neural networks. In this section, we will briefly review some of the previous work in this area.

Many studies have demonstrated the forecast ability of the traditional neural network models. For instance, [62] applies multilayer feedforward neural net-works to forecast Taiwan Dollar/US Dollar exchange rate and the results are better than ARIMA models'. The authors, therefore, conclude that the neural network approach is a competitive and robust method for the forecasting.

Another example is that [30] uses three neural-network-based forecasting models i.e. Standard Backpropagation (SBP), Scaled Conjugate Gradient (SCG)and Backpropagation with Baysian Regularization (BPR), to forecast the exchange rates of six foreign currencies against Australian dollar. The results show that all the NN-based models outperform traditional ARIMA model and SCG based model performs best.

[39] presents a forecasting model based on neural network and genetic algorithm. The results of the comparative experiments show that the new model provides significantly better performance than traditional artificial neural network and statistical time series modelling approaches.

[46] focuses on how to use evolutionary algorithms to automatically build a radial basis function neural networks for exchange rates forecasting. The results obtained in this study show an improvement of the performance over the conventional methods.

Theoretically, a hybrid model can take advantage of the strong points of both models. Therefore, some studies use hybrid model to forecast exchange rates.

[74] presents a hybrid forecasting model that combines both ARIMA and neural network approaches. The empirical results suggest that the hybrid model outperforms each of the two individual models.

Traditional learning approaches have difficulty with noisy, non-stationary time series prediction. For this reason, [16] uses a hybrid model which combines symbolic processing and recurrent neural networks to solve the problem.

A wide variety of other methods have been proposed for forecasting exchange rates: [54] compares the forecasting ability of three different recurrent neural network architectures and then devises a trading strategy based on the forecasting results to optimize the profitability of the system.

[32] proposes a multistage neural network meta-learning method for forecasting US Dollar/Euro exchange rate. The empirical results show that the proposed model outperforms the individual ARIMA, BPNN, SVM models and some hybrid models.

[15] examines the use of Neural Network Regression (NNR) models in forecasting and trading the US Dollar/Euro exchange rate. The authors demonstrated that NNR gives batter forecasting and trading results than ARMA models.

Wavelet neural network have been widely-used for forecasting oil prices [69], stock index [4], electricity demand [19] [72] [73] and other time series. But there are not many applications of wavelet neural network for exchange rate forecasting. [53] is an example, in this study, the author proposes a hybrid model which combines Wavelet Neural Network and Genetic Algorithm for forecasting exchange rates. The experimental results show that the proposed method provides satisfactory performance for different forecasting horizons and, strangely the author claims that the accuracy of forecasting does not decline when the forecasting horizon increases.

The result of empirical study shows that Wavelet Neural Network model give better results for time series forecasting than other models . The comparison study of forecast accuracy show that the first procedure (with stepwise) of non-stationary time series yields the best forecast compared to ARIMA, MAR and WNN models by using other procedures. It's showed by the smallest RMSE at testing data[49].

The back-propagation neural network (BPNN) model and the wavelet neural network (WNN) model were compared by the crisis forecasting accuracy and in-sample and out-of-sample test. The results showed that WNN model could be applied to the currency crises could effectively capture the economic variables associated with the currency crises, and might be to provide a more powerful tool for macroeconomic time series data[70].

3. Justification of the proposed work:

The field of Wavelet Networks is new, although some sporadic and isolated attempts have taken place in recent years to build a theoretical basis and applications to various fields. There is tremendous potential for its application to new and exciting areas. The potential of wavelet networks in engineering, economics, medical sciences and social science is rich and still growing. Wavelet-based methods represent good alternatives to other methods. From our point of view, the wavelet neural network is especially suitable for forecasting, because wavelets can "decompose economic time series into their time scale components" and this is "a very successful strategy in trying to unravel the relationship between economic variables [84]." Furthermore, previous research such as [3], [21] and [49] has shown that using economically significant variables for inputs can improve the performance of the forecasting model. Therefore, we came up with an idea of combining wavelet neural network with economically meaningful variables to achieve accurate forecasting.

4. Aims & Objectives:

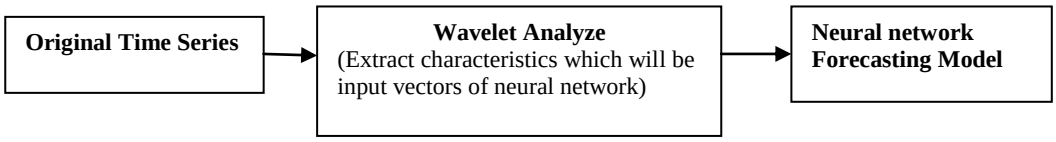
Motivated and inspired by the work on wavelet neural networks, our main interest in this research is to develop a forecasting model based on wavelet neural networks and we shall study the following financial time series applications the context of Indian market:

1. Foreign Exchange Rate.
2. Inflation Rate.
3. Jobless Rate .
4. Growth rate (GDP) rate.
5. Indian IT Industry Growth Rate.

5. Methodology proposed to be followed:

For the proposed investigation we shall be developing a forecasting model based on the wavelet neural networks.

Frame Work of the Model


Original Time Series
Wavelet Analyze
(Extract characteristics which will be input vectors of neural network)
Neural network Forecasting Model

Proposed Methodology:

1. Decompose original time series using wavelet decomposition and obtain the corresponding approximation and details series at a predetermined level of resolution .

2. Design neural network predictive model for each of the decomposed components of the original time series

3. Input variables of the neural network models for each of the decomposed series, comprising of technical indicators

4. Use the model for arriving at the results.

5. Conduct a series of comparative analysis to evaluate the performance of our model as compared with others' work. Finally, we will present and discuss the results.

6. Possible Outcome of the investigation:

An improved forecasting model based on wavelet neural network for financial time series applications. We shall compare the new model's performance with other previous studies. Our experimental results should indicate that the proposed model provides much better forecasting results than existing methods. Therefore, the work should demonstrate the feasibility of combining wavelet and neural network to achieve accurate forecasting.

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